Journal of Research in Business, Economics and Management (JRBEM)
ISSN: 2395-2210

SCITECH
RESEARCH ORGANISATION

Volume 5, Issue 4
March 5, 2016

Journal of Research in Business, Economics and Management
www.scitecresearch.com

Rationalizing an Econometric Test Model: An Empirical Investigation of ARCH Family Models

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Abstract

Selecting an appropriate econometric testing model is of high value to scholars of this field. The central focus of this paper is to empirically investigate the rationality and appropriateness of an econometric testing model for time series macroeconomic variables that exhibit clustering volatility. We test the India's Producer Price Index (PPI) covering the period January 01, 1947 to October 30, 2015 arranged on monthly basis by using the ARCH family models. The empirical investigation and statistical analysis show that among ARCH, GARCH, TARCH, PARCH and EGARCH models, the most rationale and appropriate testing model for PPI and as such variables that share common nature is the GARCH model as its statisitical result displays lower values for AIC, SIC and HIC that positively correspond with theoretical foundation of the econometric literature and satisfy the philosophical requirements.

Keywords: ARCH; GARCH; TARCH; PARCH; EGARCH; PPI.

1. Introduction

Estimating large univaraite and multivariate time – varying covariance and matrices have become an interesting subject for many scholars around the globe. The variation in selecting an appropriate model of testing for covariance of macroeconomic time series variables such as inflation, PPI, CPI, GDP, GNI, GNP, unemployment and so on is a research concern while the unification of it is also another topic of concern. The ARCH family models are widely used by researchers for time series data when there is an assumption or any reason to believe that the data error term or innovation arises due to the function of previous period's error terms. The basic model has been developed by Engle (1982) and many other acronyms have so far been added to the basic structure of ARCH such as; GARCH, IGARCH, EGARCH, TARCH, PARCH NGARCH, QGACRH and COGARCH. The models fit best with time series data that exhibit clustering volatility (Enders, 2004). An extensive review of literature shows that different ARCH family models are used by researchers on as such data that share common nature (see for instance, Bhaskara & Rao 2006; Bonomo et.al., 2003; Cont, 2007; Gaunersdorfer & Hommes, 2007; Gonzalez & Gimeno, 2012; Miles, 2008; Plosser, 2009; Chit et.al., 2010; Klaassen, 2002; Marcucci, 2005). Brooks (2007) uses the APARCH model to test the developed market equity and states that APARCH is useful in modelling the leverage and asymmetry effects; power transformations and long memory; and non-normal conditional error distributions that characterize the data. Daal et.al. (2007) recognizes that asymmetric GARCH-Jump model synthesizes the autoregressive jump intensities and volatility feedback in the jump component and further shows that the model better fits for the dynamics of the equity returns in the US and emerging Asian markets, irrespective whether the volatility feedback is generated through a common GARCH multiplier or a separate measure of volatility in the jump intensity function. McKenzie et.al. (2001) applies PARCH model to investigate the clustering volatility of future commodity data while Krämer (2008) considers that GARCH (1.1) derives sufficient conditions for the square of the process to display long memory and provides some additional intuition for the empirical observation that estimated GARCH-parameters often sum to almost one. In this paper, we intent to apply most of the ARCH family models on India's PPI that exhibits clustering volatility and empirically investigate the most rationale and apprpriate model among the ARCH family for as such data that share common nature. The remainder part of this paper is organized as follow: section 2 discusses the data and model, section 3 presents the data analysis and results and section 4 concludes the paper.

2. Data and Model

2.1 Data

In this paper, we use a set of time series data with regards to India's Producer Price Index (PPI) which is retrieved from the official website of National Bureau of Economic Research (NBER) covering the period from 01.01.1947 to 30.10.2015 arranged by monthly basis that the total adjusted observations round to 824 months for the aforementioned period. PPI is the only variable used in this paper which is treated as a control variable and is computed on a constant form.

2.2 Model

This paper is far different in nature than the other studies. Our attempt is to investigate and evidentially determine the most rationale and appropriate testing model to be used for investigating the clustering volatility of the macroeconomic variables. The satisfication of intiail requirement for our empirical investigation calls for stationarity of the variable at level or at first difference or whichever that exhbits conditional stability. To do so, we use the first difference of the natural logarithm of PPI to facilitate us in proceeding with the rest of our testing procedures. Below is a brief discussion of the empirical investigation that we use in this paper:

2.2.1 Ordinary Least Square

The OLS is computed on constant form on the base of which the rest of ARCH family models (ARCH, GARCH, TARCH, PARCH and EGARCH) are tested. The OLS equation fits with our data is written as:

$$dlnppi_t = plnppi_{t-1} + \varepsilon_t \tag{1}$$

let ε_t be the independent and specifically distributed as $N(0,\sigma^2)$ and OLS regression be based on the number of observation in time series data of the autocorrelation given by p as:

$$\hat{\rho}_n = \frac{\sum_{t=1}^{n} dlnppi_t \text{ - } 1lnppi_t}{\sum_{t=1}^{n} dlnppi_t^2} \tag{2}$$

where if $|\rho| < 1$ then $\sqrt{n}\left(\hat{\rho}_n - \rho\right) \to N\left(0, 1 - \hat{\rho}^2\right)$ and by getting a valid result, then the result would have a variance = 0 (Azimi, 2015). On the basis of OLS computation, we continue our investigation by running ARCH family models one by one to facilitate a comparative analysis of the statistical results. The theoretical foundation for selecting the most rationale and suitable model among the ARCH family models is the one which shows lower AIC (Akaike Information Criteria), SIC (Schwarz Information Criteria) and HIC (Hannan Information Criteria) values.

2.2.2 ARCH Model

The ARCH or Auto-Regressive Conditional Heteroskedasticity mean with an auto-regressive or AR(1) first order and first order variance is used consistently for which, we fit the following two equation:

$$y_t = a_0 + a_1 y_{t-1} + \varepsilon_t \tag{3}$$

$$h_t = \omega + \alpha_1 \hat{\varepsilon}_{t-1}^2 \tag{4}$$

where the first equation is computed for the mean model and the second equation represents the conditional variance model of ARCH. Along with this, the testing continues to check whether there is ARCH or GARCH effect in the residuals for which the following equation is used:

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \tag{5}$$

where β is the coefficient of the model and if the sum of coefficient equals to zero means that there is no ARCH effect in the residual or $\sum_{i=1}^{q} \alpha\varepsilon_{t-1}^2 + \sum_{i-1}^{p} \beta_i h_{t-1} = 0$ or vise versa. Moving to the next ARCH family model is the computation of GARCH model which is discussed below.

2.2.3 GARCH Model

GARCH or Generalized Auto-Regressive Conditional Heteroskedasticity with an explanatory variable is computed on (1, 1) means one ARCH and one GARCH order. The equation we fit is expressed as:

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \gamma_1 y_t \tag{6}$$

In the equation above, y_t is the explanatory variable (in our case the explanatory variable is the constant and we only use one dependent variable so called PPI) provided that the variable is generated from a stationary process at level or it becomes stationary at first difference.

2.2.4 EGARCH

EGARCH or Exponential Generalized Conditional Heteroskedasticity is computed to investigate the possibility of positive response to shocks. The EGARCH (1, 1) equation with q and p is expressed as follow:

$$\log h_t = \omega + \sum_{i=1}^{q} [\theta_1 \varepsilon_{t-1} + \theta_2 \left(|\varepsilon_{t-1}| - E\left\{ |\varepsilon_{t-1}| \right\} \right) + \sum_{q=1}^{p} \beta_i \log h_{t-1} \tag{7}$$

Where in the equation above, there are two parameters as the first $(\theta_1 - \theta_2)$ shows the response to positive shocks within the ε_{t-1} and the second one $(\theta_1 - \theta_2)$ is associated with the critical value indicating the negative effects of the shocks in ε_{t-1}. In the computation of EGARCH model, it is assumed that the residuals are normally distributed.

2.2.5 TARCH Model

TARCH or Threshold Auto-Regressive Conditional Heteroskedasticity is almost the same as the GARCH model but with a minor difference that we add one threshold order and the equation we fit is written as:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \delta \varepsilon_{t-2}^2 + \beta \sigma_{t-1}^2 + \rho REC_1 \tag{8}$$

where $d_t = 1$ if the $\varepsilon_t < 0$. As stated above, the model is almost the same as the GARCH but this extension allows for positive response to shocks represented by α and negative shocks effect is represented by $\alpha + \gamma$ on future volatility running from the variable.

2.2.6 PARCH

PARCH or Power Auto-Regressive Conditional Heteroskedasticity which is mostly called Power ARCH is a recent addition to the ARCH family of econometric models introduced by Ding et.al., (1993) wherein the power term by which the data is transformed was estimated within the model rather than being imposed by the researcher (McKenzie et.al., 2001).

$$\sigma_t^{\delta} = \omega + \beta \sigma_{t-1}^{\delta} + \alpha \left(|u_{t-1}| - \gamma u_{t-1} \right)^{\delta} \tag{9}$$

Where γ presents the leverage parameter and $\gamma > 0$ implies the leverage. By computing the PARCH model, we empirically investigate the lower values of AIC, SIC and HIC in the generated values from all the five models of the ARCH family. Once the stated lower values are identified, the autocorrelation function is used to test the null that there is no serial correlation in residuals of the selected model against the alternative.

2.2.7 Test of Autocorrelation

Since, there is a possibility of serial correlation in residuals within the series. We compute the standardized residual squared representing the autocorrelation function (ACF) and partial correlation function (PACF) to test the null hypothesis that there is no autocorrelation in the residuals against the alternative. The equation for ACF and PACF on SRS can be written as:

$$\tau_k = \frac{\sum_{t=1+k}^{T} \left(Y_t - \bar{Y} \right)\left(Y_{t-k} - \bar{Y} \right)}{\sum_{t=1}^{T} \left(Y_t - \bar{Y} \right)^2} \tag{10}$$

The above equation exhibits the ACF of a series Y at the lag of k, while $\bar{Y}$ is the sample mean for Y. The PACF which is simultaneously computed along with ACF for testing the null can be expressed as:

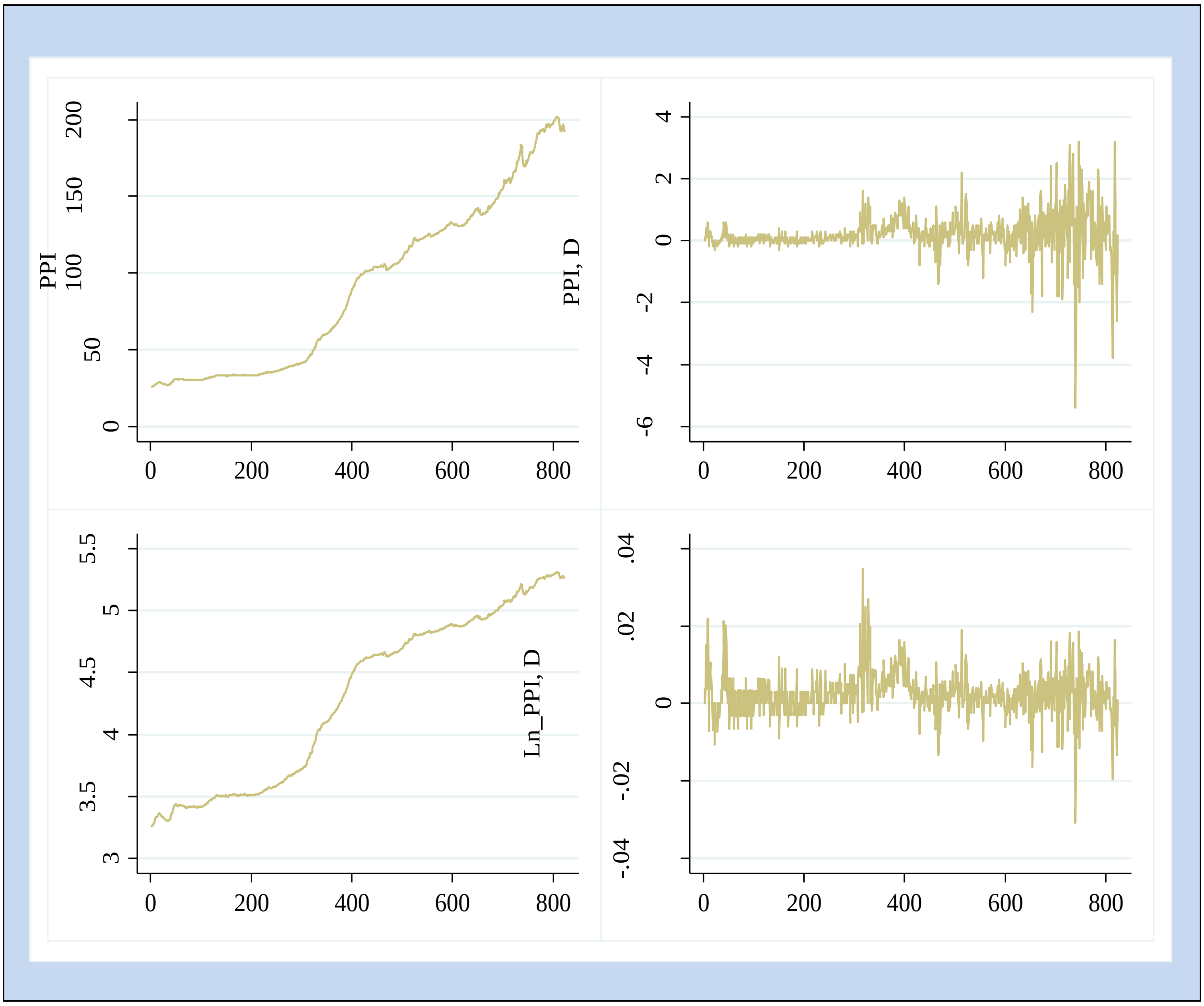
$$\phi_k = \begin{cases} \tau_1 \\ \dfrac{\tau_k - \sum_{j=1}^{k-1} \phi_{k-1,j}\tau_{k-j}}{1 - \sum_{j=1}^{k-1} \phi_{k-1,j}\tau_{k-j}} \end{cases} \tag{11}$$

The acceptance of null hypothesis that there is no ARCH effect in the residual shows that the model is nicely fitted with our variable so called D.Ln_PPI. We continue our test for the normal distribution of the residuals within the series. We plot the standardized quantile with a line of t-distribution to check for any deviation of the residuals from the stated line so that an accurate conclusion is drawn.

3. Data Analysis And Results

This paper is far different than the rest of articles in econometric field and approaching to a rationale result on which we can conclude the paper requires consertive comparison among different ARCH family models. Keeping this and the testing procedures specified in section 2 into account, this section provides the results and discussion of the paper. To begin with, the variable (PPI) must be tested for its stationarity on which the rest of computation can be made (see, figure 1).

Figure 1: PPI at Level and First Difference



PPI (Producer Price Index) is plotted on its total number of observation arranged by monthly basis which represents the period 01.01.1947 to 30.10.2015 and exhibit a strong upward slop at level which means that this is non-stationary while the stated variable at first difference shows stationarity. For evaluating a rationale model among ARCH, GARCH, TARCH, PARCH and EGARCH the variable should be stationary at level or at first difference. On the other hand, the variable at natural logarithm and at level also shows nonstationarity where its first difference shows a better volatility than original variable at first difference. Therefore, PPI at log and at its first difference (Ln_PPI, D) is used for further computations.

Table 1: OLS Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.002434	0.000201	-12.12103	0.000***
R-squared	0.000000	Mean dependent var		0.002434
Adjusted R-squared	0.000000	S.D. dependent var		0.005760
S.E. of regression	0.005760	Akaike info criterion		-7.474418
Sum squared resid	0.027275	Schwarz criterion		-7.468691
Log likelihood	3076.723	Hannan-Quinn criter.		-7.472221
Durbin-Watson stat	1.298925			

***0.01, **0.05, *0.10
Sample: 01.01.1947 to 30.10.2015

The ordinary least square regression is run to take the constant as an explanatory variable for the PPI being the dependent variable in this paper. Since, further computation is based on only one dependent variable, taking constant as an explanatory variable makes the process much easier to proceed and controls for regression spuriousness[i]. The OLS regression is also computed on first difference of natural log of the Producer Price Index so called (Ln_PPI, D).

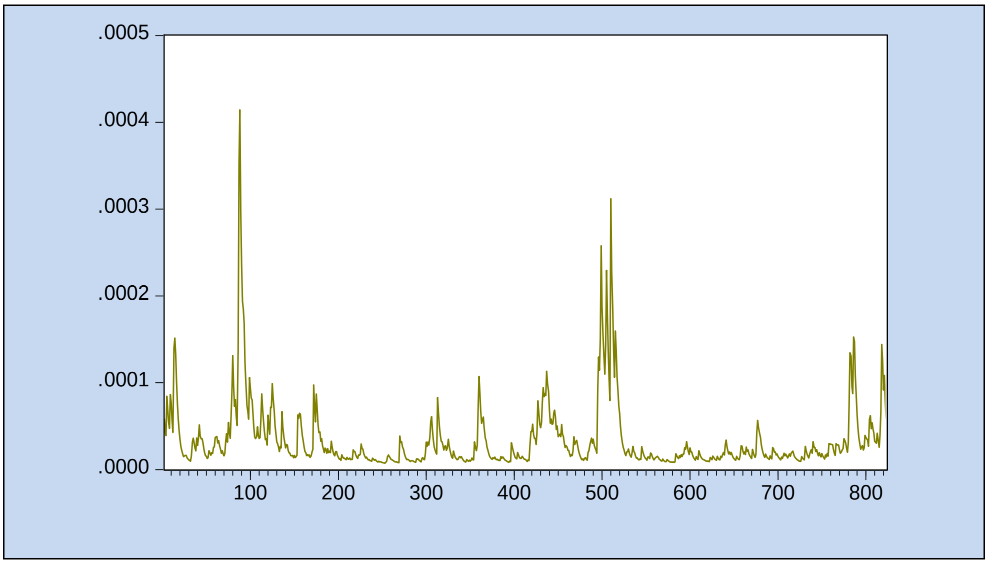
Table 2: ARCH Family Comparison

Variable	ARCH Family Models Comparative Analysis				
D.Ln_PPI	ARCH Model	GARCH Model	TARCH Model	PARCH Model	EGARCH Model
Coef.	-0.002030	-0.001861	-0.001858	-0.002006	-0.002016
Std. Err.	0.000129	0.000158	0.000161	0.000143	0.000147
Z(t)	-15.73225	-11.80053	-11.57271	-14.06356	-13.69684
Prob.	0.0000	0.0000	0.0000	0.0000	0.0000
R-Squared	-0.004913	-0.009902	-0.009988	-0.005527	-0.005263
Adjusted R	-0.004913	-0.009902	-0.009988	-0.005527	-0.005263
AIC	-7.677667	-7.788148***	-7.785801	-7.785808	-7.780494
SIC	-7.660488	-7.765242***	-7.757168	-7.757175	-7.751861
HIC	-7.671077	-7.779360***	-7.774816	-7.774823	-7.769509

***Significant if AIC, SIC and HIC <
Pre-sample Variance: Backcast (parameter = 0.7)
Sample: 01.01.1947 to 30.10.2015
Total Observation: 824

In table 2 we present the statistical analysis of five ARCH family models in which the approach is that lower the values of Akaike Information Criteria (AIC), Schwarz Information Criteria (SIC) and Hannan Information Criteria (HIC), the better fitted model for a particular variable will be. Considering the negative sign of the statistical result of all the models stated herein, we understand that GARCH (Generalized Auto-Regressive Conditional Heteroskedasticity) model exhibit significant values of AIC, SIC and HIC by -7.788148, -7.765242 and -7.779360 respectively and show that GARCH model is the most suitable econometric test model for PPI, though, some researchers ignore the negative sign of criterion values that in such case, the selection of best fitted model is in reverse order. On the other hand, ARCH (Auto-Regressive Conditional Heteroskedasticity) provides statistical values for AIC, SIC and HIC by -7.677667, -7.660488 and -7.671077 that are greater than the GARCH model statistical values we discussed. The statistical values of AIC, SIC and HIC for TARCH (Threshold Auto-Regressive Conditional Heteroskedasticity), PARCH (Power Generalized Conditional Heteroskedasticity) and EGARCH (Exponential Generalized Conditional Heteroskedasticity) are all greater than values of AIC, SIC and HIC computed and presented for ARCH model. This means that the most suitable and nicely fitted model to investigate the clustering volatility of PPI is the GARCH model (below, we present the residual graph which is generated after GRACH computation on D.Ln_PPI).

Figure 2: Conditional Mean for GARCH Model



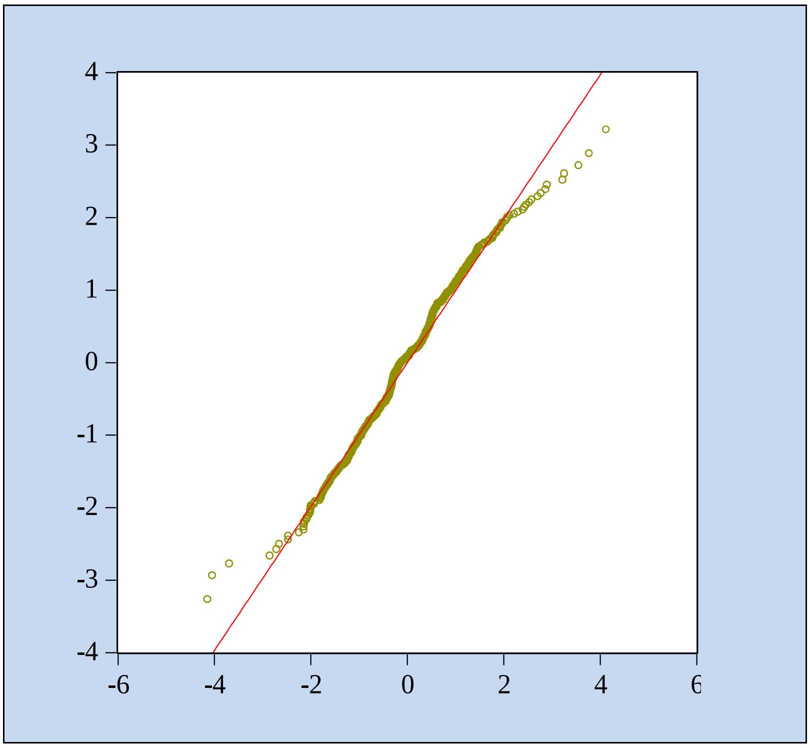
<table>
<tr><th colspan="7">Table 3: Test for Autocorrelation
Null: There is no autocorrelation in the residuals Vs. Alternative: There is autocorrelation in the residuals</th></tr>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>P-Value</th></tr>
<tr><td>.| |</td><td>.| |</td><td>1</td><td>0.052</td><td>0.052</td><td>2.2662</td><td>0.132***</td></tr>
<tr><td>.| |</td><td>.| |</td><td>2</td><td>-0.038</td><td>-0.041</td><td>3.4680</td><td>0.177***</td></tr>
<tr><td>.| |</td><td>.| |</td><td>3</td><td>-0.020</td><td>-0.016</td><td>3.7946</td><td>0.285***</td></tr>
<tr><td>.| |</td><td>.| |</td><td>4</td><td>0.004</td><td>0.004</td><td>3.8065</td><td>0.433***</td></tr>
<tr><td>.| |</td><td>.| |</td><td>5</td><td>0.022</td><td>0.021</td><td>4.2184</td><td>0.518***</td></tr>
<tr><td>.| |</td><td>.| |</td><td>6</td><td>-0.026</td><td>-0.028</td><td>4.7819</td><td>0.572***</td></tr>
<tr><td>.| |</td><td>.| |</td><td>7</td><td>-0.032</td><td>-0.028</td><td>5.6420</td><td>0.582***</td></tr>
<tr><td>.| |</td><td>.| |</td><td>8</td><td>0.000</td><td>0.002</td><td>5.6420</td><td>0.687***</td></tr>
<tr><td>.| |</td><td>.| |</td><td>9</td><td>0.009</td><td>0.006</td><td>5.7101</td><td>0.769***</td></tr>
<tr><td>.| |</td><td>.| |</td><td>10</td><td>-0.038</td><td>-0.040</td><td>6.9004</td><td>0.735***</td></tr>
<tr><td colspan="7">***Significant to accept the null if $p \geq 0.05$</td></tr>
</table>

There are two issues in the table above 1) the slow decay in the residuals both in ACF and PACF shows the stationarity of the residuals predicted after the GARCH model and 2) the corresponding p-values at 10 lags are all > ∂ 0.05 that are significant to accept the null hypothesis that there is no serial correlation in the residuals. Thus, it documents that the selected model for the assessment of PPI is nicely fitted.

Table 4: Heteroskedasticity Test: ARCH Null: The residuals are homoscedastic Vs. Alternative: The residuals are heteroskedastic			
F-statistics	2.257361	Prob. F(1,820)	0.3046***
Obs*R-squared	2.256654	Prob. Chi-square(1)	0.3040***
*****Significant to accept the null if $p \geq 0.05$**			

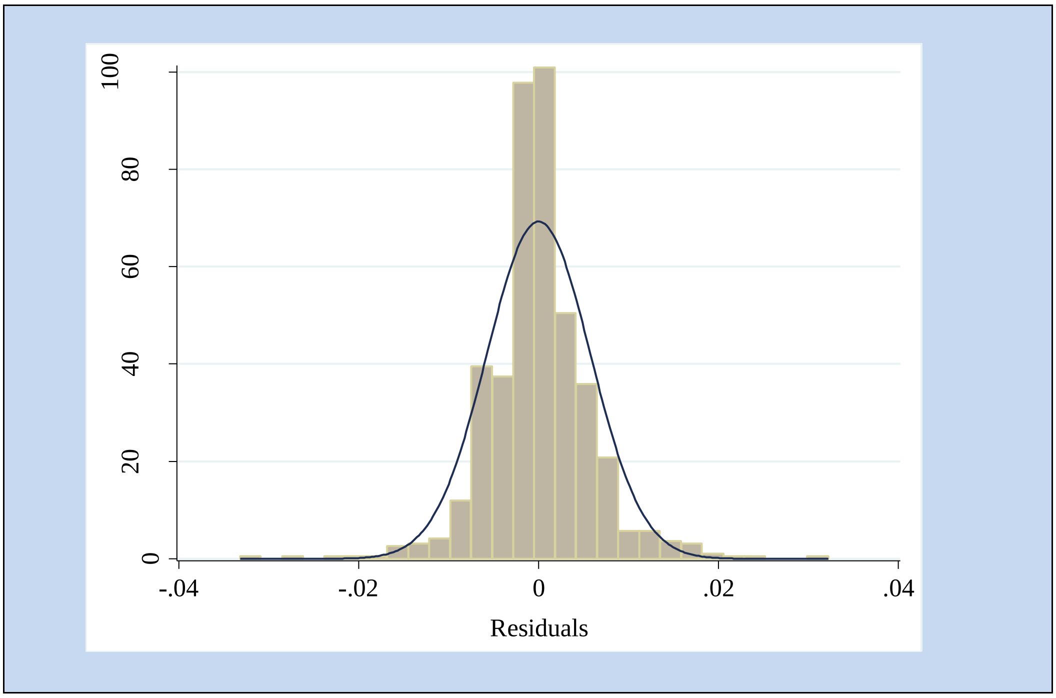
The corresponding probability value of both F-statistic and Chi-square being 0.3046 and 0.3040 are significant meaning that both values are more than ∂ 0.05. Since, the residuals are homoscedastic, we accept the null hypothesis against the alternative.

Figure 3: Quantile of Normal Residuals



The figure above represents a t-distribution line along with the following residuals on or around the straight line. It seems that there is a very small deviation of the residuals from the line but major parts of residuals are following the right path alongside the straight line which shows the normal distribution of the residuals. Therefore, the plot suggests that with exception of large negative shocks, the residuals are utmost random and normal in distribution.

Figure 3: Jarque-Bera Test of Normality

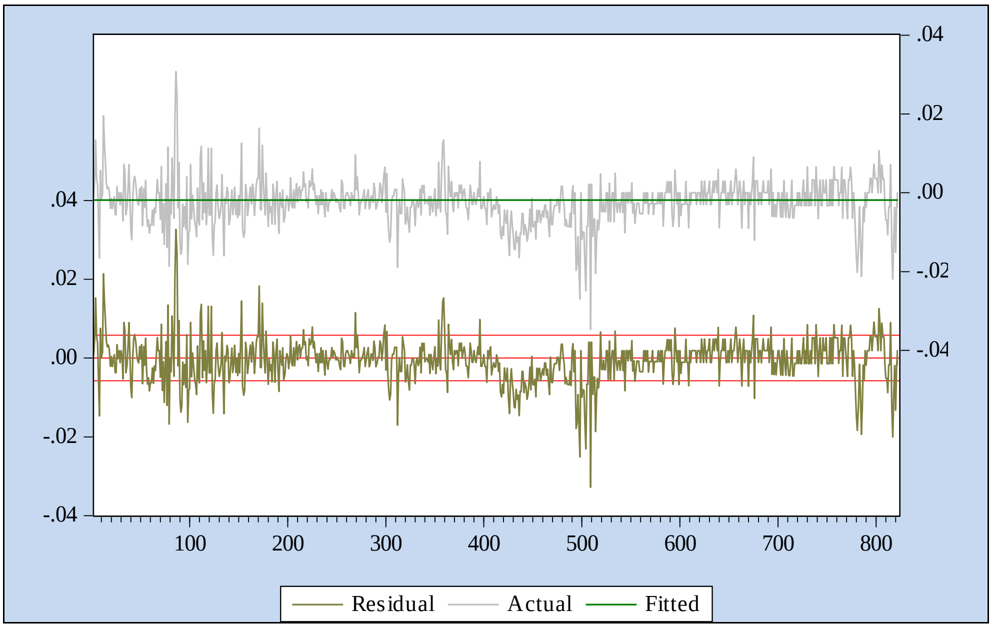


***Significant to accept the null if $p \geq 0.05$

Jarque-Bera *p*-value: 0.2311***; Skewness *p*-value: 0.1719***; Kurtosis *p*-value: 0.2843***

The Jarque-Bera Test of normality exhibit corresponding probability values of 0.2311, 0.1719 and 0.2843 for JB, SK and KU respectively that are significant to accept the null hypothesis that the residuals are normally distributed and to reject the alternative. This shows that residuals are random and normal in distribution which is very desirable for all the process of our test model we applied herein. As the final step to conclude the paper, we test whether the residuals of the test of normality and Skewness is stationary for which the following graph is plotted upon the stated residual:

Figure 4: Residual Stationarity



As it is recently discussed, figure 4 is plotted on the residual of the GARCH model to test the null hypothesis that the residual is stationary and does not follow unit root. The figure represents two parts that the first (upper) one is the actual residual shown by light grey color. This shows that the actual variable or PPI is stationary while the second part (lower) one also exhibit a line of stationarity which is desirable for our test on the basis of which we cannot reject the null hypothesis rather we accept and conclude that the residual is stationary and does not follow unit root. It should also be noted that actual variable is computed on its first difference and one of the reason that the residual shows stationarity after the test of normality is based on the actual variable which is converted into first difference of its natural logarithm. Yet it does not affect the overall conclusion of the paper, though, it is worth to be realistic.

4. Discussion and Conclusion

Extensive review of literature reveals different approaches in investigating the clustering volatility of the macroeconomic variables used by a sheer number of authors who publish their papers in the fields of econometric, economics and financial time series analysis (see for instance, Besag & Diggle, 1977; Bonomo et.al., 2003; Chang & McAleer, 2015; Chit et.al., 2010; Daal et.al., 2007; Gaunersdorfer & Hommes, 2007; Glosten et.al., 1993). There is no doubt that neither PPI is same in all countries nor it moves at the same direction and order but it is obvious that it shares common nature with regards to specificity of a dependent variable so called the Producer Price Index (PPI). Another matter of concern is the existing of serial correlation in the residuals of such variables that sometimes it results that authors switch to inappropriate ARCH family model. In this paper, we test all the ARCH family models with regards to serial correlation and normality of the residuals' distribution that as a direct consequence of which, all the stated models are positive and are satisfying the conditional requirements but in relation to our theoretical foundation based on lower value of AIC, SIC and HIC, GARCH model is the most rationale, suitable and appropriate testing model for PPI variable.

In this paper, we empirically examine the appropriateness, rationality and suitability of ARCH family models such as ARCH mean, GARCH (1, 1), TARCH (1, 1, 1), PARCH (1, 1, 1) and EGARCH (1, 1, 1) in testing the clustering volatility of Producer Price Index (PPI) relating to Indian Economy. The statistical analysis obtained from the computation of the stated ARCH family models and on the basis of our theoretical foundation, it is found that Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH) model is a rationale and nicely fitting model for assessing and investigating the clustering volatility of PPI as it exhibits lower statistical value for AIC, SIC and HIC than ARCH, TARCH, PARCH and EGARCH models.

The variable PPI used in this study relates to India for period 01.01.1947 to 30.10.2015 and the model which is recommended to be used for further studies also relates to the same nature variables. Therefore, its applicability may not be generalized.

Acknowledgment

The author takes the opportunity to acknowledge the valuable and constructive comments of the anonymous referees and the initial formatting editor of Research Department of Rana University.

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Author's Biographical Notes

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[i] A regression might be spurious when there are two variables exhibit unit root or nonstationarity at level and the value of the R-Squared is greater than the estimated value for Durbin Watson. To control for this, we use the Log Difference of the variable PPI. By this, the value for R-Squared is 0.00000 < 1.298925 value of the Durbin Watson meaning that this regression is not spurious and is valid to facilitate the rest of our empirical investigation for ARCH family models.